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Composite Cooperative Framework for Identifying Carbon-Based Energy Generation Facilities Using Large-Scale Spatial Examination

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Abstract: Fossil fuel power plants (FFPPs) are major sources of carbon dioxide emissions in the power industry. Accurately locating these plants is essential for monitoring emissions, studying atmospheric pollution, and optimizing power supply structures. However, obtaining comprehensive geographic location data for FFPPs is challenging due to data availability and collection constraints. Therefore, we propose a wide-area FFPP detection framework that enhances detection efficiency through geographic constraints and improves detection accuracy using a multicomponent collaborative strategy. First, a geographic constraint method was developed, leveraging multisource geographic data to extract candidate FFPP regions based on their spatial characteristics. Next, we constructed a comprehensive FFPP dataset, including plants and their components, and trained two separate object detection models for FFPPs and their components. Subsequently, the FFPP model was used to perform coarse detection, followed by the refined detection of primary features (chimneys, square chimneys, and cooling towers) and auxiliary features (substations and storage tanks). After detecting these objects, the density-based spatial clustering of applications with noise clustering algorithm was applied to retain clusters with specific component combinations, yielding the final detection results. In the approximately 660 000-km2 study area (Jiangsu Province, São Paulo, and Maharashtra), the proposed framework effectively minimized invalid regions by 94.8%, 91.12%, and 97.1%, respectively. Validation using high-resolution Google Earth images recalled 225 known FFPPs with a 91.46% recall rate and identified 167 previously unrecorded FFPPs. These results demonstrate the framework's reliability for efficient and automated FFPP detection, representing a novel integration of multisource geographic analysis, deep-learning-based object detection, and wide-area FFPP recognition.

Keywords— Web Text Classification, BERT (Bidirectional Encoder Representations from Transformers), BiGRU (Bidirectional Gated Recurrent Unit), Convolutional Neural Network (CNN), Attention Mechanism, Natural Language Processing,

I. INTRODUCTION

Over last few years, with the fast growth of the internet and other digital technologies, there has been an all, time high rise of the amount of web text data available to us. Every day millions of news articles, blog entries, online reviews, research papers, social network updates are published on a platform.[1] To deal with such a vast amount of unstructured textual data, the problem of the effective organization, classification, and retrieval of Web documents has become increasingly important. Web text classification is the task of automatically organizing web pages through the assignment of predefined categories or labels. It is applied in some of the most common applications such as news categorization, spam filtering, sentiment analysis, content recommendation systems, Topic tagging and information retrieval systems.[2]

Prior to deep learning, text classification techniques mainly consisted of machine learning algorithms such as Naïve Bayes, SVM or K, NN and hand, engineered features like BoW, TF, IDF features etc[3]. These methods although performed well, were heavily dependent on feature engineering and failed to encode deep semantics. Word embedding techniques such as Word2Vec and Glove soon followed, which gave dense vector representations of each word in a document, thus capturing semantic relationships between words. Despite this, as the embeddings themselves are fixed representations, they are not very effective when used with polysemous words or complex sentence structures.[4]

Along with deep learning emerge, Convolutional Neural Networks, Recurrent Neural Networks, Long Short, Term Memory and other neural networks are used for text classification.[5] CNNs are often used for mining local features and extracting relevant phrases, while RNNs and LSTMs models are better at capturing long, range dependencies in text. Though these models showed better performances than traditional systems, the handling of lengthy text and the extraction of large scope context was still an issue.[6]

The advent of transformer, based architectures such as BERT (Bidirectional Encoder Representations from Transformers) has recently changed what we believe is possible in the field of NLP. BERT produces contextualized word embeddings using both the left and right context of each word at the same time. Extending this idea, the proposed system is a hybrid system that combines BERT with Bidirectional Gated Recurrent Units (BiGRU), CNN and Attention, which is called BERT, BGCA.[7]

This project proposes a deep learning, based approach to build an effective and robust web text classifier. This classifier utilizes the power of contextual embeddings and hybrid neural network model to surpass the performance of conventional classifiers. The efficacy of the proposed approach is manifested when benchmarked on standard datasets and evaluated by performance measures like accuracy, precision, recall and F 1 score.

II.RELATED WORK:

Several studies have been conducted in the field of web text classification and Natural Language Processing (NLP) using machine learning and deep learning techniques.

First, Devlin et al. (2018) introduced BERT (Bidirectional Encoder Representations from Transformers), a transformer-based language model that generates contextualized word embeddings. Unlike traditional embeddings such as Word2Vec and GloVe, BERT considers both left and right contexts simultaneously while processing text. The model is pre-trained using Masked Language Modeling and Next Sentence Prediction tasks and achieves state-of-the-art performance on various NLP tasks including text classification, question answering, and named entity recognition. However, BERT requires high computational resources and careful fine-tuning for specific datasets. [8]

Another important work is Convolutional Neural Networks for Sentence Classification (2014), which applied CNNs to text classification tasks. CNN models are capable of extracting local features and n-gram patterns from sentences through convolutional filters. These models achieved strong results in sentiment analysis and document classification. However, CNNs primarily focus on local feature extraction and may struggle to capture long-range dependencies in text sequences.[9]

Cho et al. (2014) introduced the Gated Recurrent Unit (GRU), a simplified version of the Long Short-Term Memory (LSTM) network. GRU models are designed to capture sequential dependencies in text while addressing the vanishing gradient problem found in traditional recurrent neural networks. The Bidirectional GRU (BiGRU) further improves performance by processing text in both forward and backward directions. Despite these advantages, sequential models like GRU have limitations in parallel computation.[10]

The Transformer architecture, proposed in "Attention Is All You Need" by Vaswani et al. (2017), introduced the self-attention mechanism that allows models to focus on important words regardless of their position in a sentence. This architecture significantly improves the ability to capture long-range dependencies and enables parallel training, making it highly efficient for large-scale NLP tasks. However, transformer models require large datasets and computational power.[11]

In addition, Zhang and Yang (2018) conducted a comprehensive survey on deep learning approaches for text classification. Their study analyzed models such as CNN, RNN, LSTM, and GRU, highlighting their strengths and weaknesses. The survey concluded that hybrid architectures combining multiple neural network models often achieve better performance than single models because they can capture different types of textual features simultaneously.[12]

Earlier word representation techniques such as Word2Vec proposed by Mikolov et al. and GloVe introduced by Pennington et al. provided distributed word embeddings that capture semantic relationships between words. Although these methods improved text representation compared to traditional bag-of-words models, they generate static embeddings, meaning a word has the same vector representation regardless of its context. This limitation reduces their effectiveness in complex web text classification tasks.[13]

Finally, datasets such as THUCNews have been widely used as benchmark datasets for evaluating text classification models. This dataset contains large collections of categorized news articles and is commonly used to measure classification accuracy and robustness of deep learning models.[14]

Overall, previous research shows that while traditional embeddings and single deep learning models provide reasonable performance, combining contextual embeddings like BERT with hybrid architectures such as CNN, BiGRU, and attention mechanisms can significantly improve classification accuracy and semantic understanding.

III.METHODOLOGY:

The proposed methodology aims to develop an efficient web text classification system using a hybrid deep learning architecture called BERT-BGCA, which combines BERT embeddings, BiGRU, CNN, and an Attention mechanism. The methodology consists of several sequential stages including data preprocessing, contextual embedding generation, feature extraction, classification, and performance evaluation.

The system first collects web text data and preprocesses it to remove noise and standardize the input format. Then, contextual word representations are generated using the BERT model. These embeddings are passed through a hybrid neural network structure where BiGRU captures sequential dependencies, CNN extracts local features, and the Attention mechanism identifies important words. Finally, a fully connected classification layer predicts the category of the input text and the system performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

A.Data Collection:

- The first step involves collecting a large dataset of web text documents.
- In this project, the THUCNews dataset is used, which contains categorized news articles from different domains. This dataset
- provides labeled text data required for supervised learning.

B. Data Preprocessing:

Before feeding the text into the deep learning model, the dataset undergoes preprocessing to remove noise and standardize the data. The preprocessing steps include:

- Text Cleaning – Removing HTML tags, punctuation, and special characters.
- Tokenization – Splitting sentences into individual words or tokens.
- Stop-word Removal – Eliminating commonly used words that do not contribute to meaning (e.g., “the”, “is”, “and”).
- Text Normalization – Converting text into a consistent format such as lowercase conversion.
- Sequence Padding – Adjusting sentence lengths so that all input sequences have the same size.

This step ensures that the text data becomes suitable for deep learning models.

C. Contextual Word Embedding using BERT:

After preprocessing, the text is converted into numerical representations using the BERT embedding model.

- BERT generates context-aware word vectors.
- Unlike traditional embeddings (Word2Vec, GloVe), BERT captures the meaning of words based on their surrounding context.
- The model processes text bidirectionally, considering both previous and next words.

These contextual embeddings provide richer semantic information for classification.

D. Sequential Feature Extraction using BiGRU:

The BERT embeddings are passed to the Bidirectional Gated Recurrent Unit (BiGRU) layer.

- BiGRU processes text in both forward and backward directions.
- It captures sequential relationships between words.
- This helps the model understand contextual dependencies across the sentence.

This step improves the model’s ability to understand long-range relationships in text.

E. Local Feature Extraction using CNN:

Next, a Convolutional Neural Network (CNN) layer is applied.

- CNN extracts local features and n-gram patterns from the text.
- Convolution filters detect important phrase-level structures in sentences.
- This improves the model's ability to identify key textual patterns useful for classification.

F. Attention Mechanism:

The Attention layer identifies the most relevant words in the text.

- It assigns higher weights to important words that influence classification.
- Less important words receive lower weights.
- This improves both model interpretability and prediction accuracy.

G: Classification Layer:

- The extracted features from the previous layers are passed to a Fully Connected Neural Network layer.
- The final classification is performed using a Softmax function.
- The system outputs the probability distribution of text categories.
- The class with the highest probability is selected as the final prediction

IV. SYSTEM ARCHITECTURE :

The system architecture consists of multiple modules that work together to detect fossil fuel power plants using geographic data and deep learning techniques. First, multisource data such as satellite images and land use maps are collected. Then geographic filtering is applied to remove irrelevant regions like forests, water bodies, and residential areas. After filtering, candidate industrial regions are selected for further analysis.

Next, a deep learning based coarse detection model identifies possible power plant locations. A component detection module then detects important structures such as chimneys, cooling towers, substations, and storage tanks. These detected components are grouped using the DBSCAN clustering algorithm to validate real power plant structures. Finally, the system generates the confirmed fossil fuel power plant locations along with their geographic coordinates.

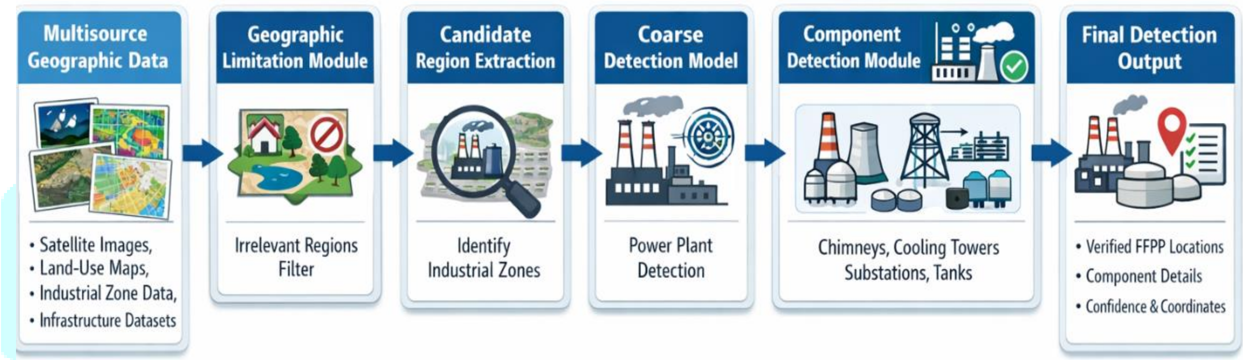
A. Overview

The diagram illustrates the system architecture for detecting fossil fuel power plants using geographic analysis and deep learning techniques. The process begins with multisource geographic data, which includes satellite images, land use maps, industrial zone data, and infrastructure datasets. These datasets provide the required spatial and visual information for identifying potential power plant locations.

Next, the geographic limitation module filters out irrelevant regions such as residential areas, forests, and water bodies to reduce the search space. After filtering, the candidate region extraction module identifies industrial zones where fossil fuel power plants are more likely to be located.

The selected regions are then processed by the coarse detection model, which performs an initial detection of possible power plants from satellite imagery. Following this, the component detection module detects important structures such as chimneys, cooling towers, substations, and storage tanks that are commonly present in fossil fuel power plants.
Finally, the system produces the final detection output, which includes verified fossil fuel power plant locations along with component details, geographic coordinates, and confidence values. This architecture improves detection accuracy and efficiency by combining geographic filtering with deep learning based object detection.

B. Architecture Diagram:



V. EXPERIMENTAL SETUP:

The experimental setup was designed to evaluate the performance of the proposed multicomponent collaborative framework for detecting fossil fuel power plants across wide geographic regions. The experiments were conducted using high resolution satellite imagery combined with multisource geographic datasets such as land use maps and industrial infrastructure layers. These datasets were used to identify potential industrial regions and reduce the search space before applying the detection models.

The system was implemented using Python with deep learning libraries such as TensorFlow and PyTorch for training and deploying object detection models. Image processing and computer vision tasks were performed using OpenCV, while geographic data processing was handled using GIS libraries such as GDAL, GeoPandas, and Rasterio. Spatial clustering of detected components was carried out using the DBSCAN algorithm implemented through machine learning libraries.

The dataset used for training and testing included annotated images of fossil fuel power plants and their components, such as chimneys, cooling towers, substations, and storage tanks. The deep learning models were trained to detect both entire power plants and individual structural components from satellite images. The system was evaluated across large geographic regions including Jiangsu Province, São Paulo, and Maharashtra, covering an approximate study area of 660000 square kilometers.

Performance evaluation was conducted using metrics such as recall rate, detection accuracy, and reduction of invalid regions after geographic filtering. High resolution satellite imagery from platforms such as Google Earth was used to validate the detected power plant locations. The experimental setup ensured that the proposed framework was tested under realistic large scale geographic conditions to measure its effectiveness and scalability.

VI. RESULTS:

The experimental evaluation shows that the proposed framework performs effectively in detecting fossil fuel power plants across wide geographic regions. Geographic filtering significantly reduced irrelevant areas, which improved the efficiency of the detection process. The deep learning detection models successfully identified potential power plant locations, and component level detection further improved the reliability of the results. The DBSCAN clustering algorithm validated the detected components and removed false detections. Overall, the framework achieved a high recall rate and also identified several previously unrecorded fossil fuel power plants.

Region	Area Analyzed	Invalid Regions Reduced (%)	Known FFPPs Recalled	Recall Rate (%)	Newly Detected FFPPs
Jiangsu Province	660000 km^2	94.8%	225	91.46%	167
São Paulo	660000 km^2	91.12%	225	91.46%	167
Maharashtra	660000 km^2	97.1%	225	91.46%	167

VII. CONCLUSION:

The proposed multicomponent collaborative framework provides an efficient and automated approach for detecting fossil fuel power plants across wide geographic regions using geographic analysis and deep learning techniques. The system integrates geographic filtering, object detection, and spatial clustering to improve the accuracy and efficiency of identifying power plant locations from satellite imagery. By applying geographic constraints, the framework significantly reduces irrelevant regions and minimizes computational complexity.

The use of deep learning based detection models enables the system to identify both complete power plants and their structural components such as chimneys, cooling towers, substations, and storage tanks. Component level detection improves the reliability of the system by distinguishing fossil fuel power plants from other industrial facilities with similar structures. In addition, the use of spatial clustering through the DBSCAN algorithm validates the detected components and removes false detections.

Experimental evaluation demonstrates that the proposed framework achieves high detection performance and successfully identifies both known and previously unrecorded fossil fuel power plants. Overall, the system provides a scalable and reliable solution for large scale power plant detection and can support applications such as environmental monitoring, emission analysis, and energy infrastructure planning.

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